Simulating Fire on the Landscape Using Markov Models

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The term disturbance has traditionally been used by ecologists to describe an event that is rare and catastrophic (e.g. Cooper 1926). More recently, that view has shifted toward one that recognizes disturbance as a natural process affecting ecosystem dynamics at many spatial and temporal scales (White 1979, Rykiel 1985, Pickett et.al. 1989).

The recent efforts to develop generalized definitions of ecological disturbance (Rykiel 1985, Pickett et.al. 1989) emphasize the hierarchical organization of ecosystems (Allen and Starr 1982). In this framework, the classification of an event as a disturbance, as opposed to a normal fluctuation, depends on both the scale of observation and the biological entity being considered. If that entity is a single tree, then the loss of several limbs during a windstorm is an exogenous disturbance affecting the physiology of the tree. If the entity of interest is a stand of trees, then the injury of a single tree becomes part of a normal fluctuation of biomass—the injury is 'absorbed' by the higher level.

The temporal scale of interest also affects the definition of disturbance. For example, on the scale of years, a single large forest fire is a disturbance to a forest landscape. However, on the scale of millenia, the change in forest structure resulting from a single fire is no longer apparent. It is more appropriate to identify the landscape structure that emerges from a fire regime. A change in structure at this level requires a change in statistical parameters such as size distributions and return intervals (Forman and Boerner 1981, Allen and Wileyto 1983). The hierarchical approach to investigating disturbance emphasizes the importance of choosing a spatial and temporal scale appropriate to both the level of organization and level of resolution of interest.

In this investigation, we are concerned with forest structure and dynamics at the landscape scale. A model of pre-settlement pattern and process at the landscape level can provide a yardstick against which to measure the current health of the ecosystem. For instance, field studies have indicated a shift in Sierra Nevada forest structure since 1900, associated with a change in fire regime (Kilgore and Taylor 1979, Stephenson et.al. 1991, Swetnam 1993). Before 1900, frequent low intensity fires burned the understory, leaving open stands with large, widely spaced trees. Since 1900, there has been a sharp decrease in forest fire frequency, and a corresponding change in stand structure to one that can support crown-fires (Weatherspoon et.al. 1992). Other effects of forest fire suppression include a disruption of the processes of seedbed preparation, nutrient recycling, and succession (Kilgore 1973).

A landscape-level vegetation dynamics model can also suggest potential effects of various land management decisions. For example, the disturbance regime across a landscape may be a vital consideration in designing wildlife reserves (Pickett and Thompson 1978, White 1992).

The structural and dynamical attributes of interest in this study include species composition; distribution of patch sizes and shapes; disturbance frequency; the effect of ecological gradients such as temperature and radiation intensity on patch distributions; the role of disturbance in creating heterogeneous habitat for wildlife; and the effect of vegetation structure on the probability and intensity of disturbance.

Existing fire models

Previous authors have taken several approaches to modeling fires in landscapes. The most detailed approach is based on Rothermel’s (1972) physical model of fire spread. Rothermel’s model was developed for forest fire managers to predict fire behavior. It is a physical model, based on an application of the law of conservation of energy to a unit volume of fuel. Because the fuel bed is assumed to be continuous and contiguous to the ground, Rothermel’s model is not intended for use in predicting the behavior of crown fires or spotting behavior.

Required inputs for Rothermel’s model include fuel characteristics, such as fuel loading, fuel depth, fuel particle surface area-to-volume ratio, heat content, particle density, moisture content, moisture of extinction, and mineral content; slope; and wind speed. Equations are then used to predict the rate of spread and intensity of the flame front.

Frandsen and Andrews (1979) used Rothermel’s equations to predict fire behavior in non-uniform fuels. They expressed the fuel types as an array of cells. The model produced a series of probability distributions of fire-spread rates and intensity. Burrows (1988) expanded on the idea of using Rothermel’s model to predict spread across a grid of non-uniform fuels. The study simulated vegetation patterns in time and space, rather than overall distributions of fire behavior. The spread of fire from a burning cell to a neighboring cell was modeled as a stochastic process, with the spread probability conditioned on the spread rate calculated using Rothermel’s model. Fuel types and slopes were allowed to vary from cell to cell, but weather conditions and fuel drying rates were assumed homogeneous throughout the landscape. Weather conditions at the time of each fire were selected at random from weather station records. Flammability was assumed to increase predictably as the vegetation grew back after a burn.

Shortcomings associated with applying Rothermel's model to the landscape

We based our first approach to simulating fire patterns in the Sierra Nevada landscape on previous spatial implementations of the Rothermel model (Frandsen and Andrews 1979, Burrows 1988). Since standardized fuel models exist to describe various stand types (Albini 1976), we focused on implementing spatial variation in fuel drying rates.

Fire managers in the United States use the National Fire Danger Rating System (NFDRS) to compute moisture for the various size classes of live and dead fuel. The moisture equations in the NFDRS (Bradshaw et. al. 1983) are based on the physics of cylindrical fuel sticks, without bark, drying off the ground, in open, south-westerly exposures. Rothermel et.al. (1986) suggested modifying weather station data on temperature and humidity to account for surface heating (due to differences among sites in aspect, elevation, canopy cover and wind). We also took this approach. If empirical relationships among solar radiation, wind, canopy characteristics, temperature, and humidity are assumed then detailed spatially and temporally explicit probability distributions of surface temperatures and humidities can be developed. These values are used to calculate the moisture content of fuels for input into Rothermel's equations for spread rate and intensity.

This approach, however, requires large amounts of data, much of which does not exist. Spatially explicit probability distributions for weather data are insufficient—the time series is important in computing drying rates. The approach also requires numerous submodels, such as models specifying surface heating rates, wind speed at the surface of a fuel bed, diurnal temperature variations, and shading by canopy cover or adjacent topography. The potential for error in both model structure and parameter estimation is correspondingly large. Furthermore, the reliability of the NFDRS drying equations themselves has been called into question (Simard and Main 1982, Anderson 1989).

Others note (Haines et. al. 1976, Burgan et. al. 1988) that none of the drying indices commonly used respond adequately to long-term drought. The 1000-hour time-lag fuel model indicates the severity of a medium-term (about four months) drought. For example, for two years, one hot and dry and the other cool and wet, Figure 1 shows the computed 1000-hour time-lag fuel moisture. Although the estimated

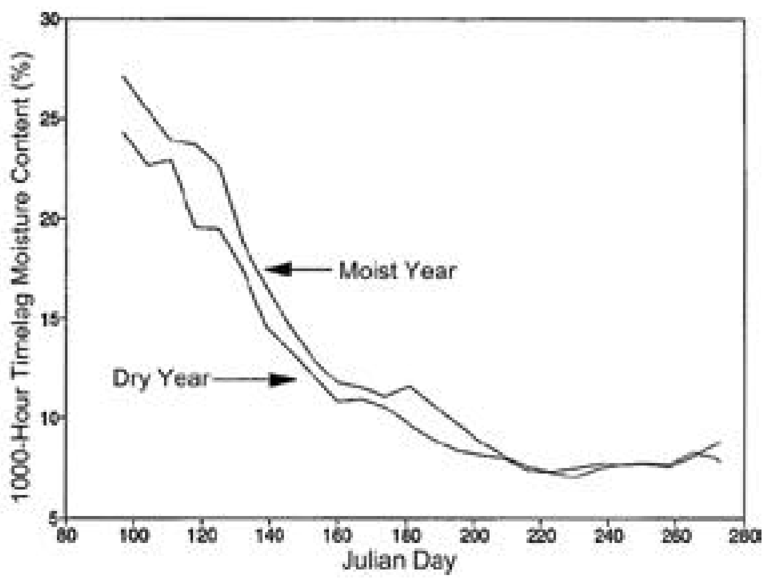

Figure 1. Estimated 1000-hour fuel moisture for a very wet and very dry year. 1000-hour fuels have the longest time-lag of any fuel elements in Rothermel's model.

1000-hour moisture content of the moist year is higher than that of the dry year for the first few months of the fire season their values converge by the end of the season. We expect, however, higher late-season fire danger during the dry year than during the wet year. More importantly, fire activities increase in hot dry years (McKelvey and Busse 1996).

There are other difficulties in modifying Rothermel’s model to simulate patterns in a complex forest ecosystem. One is grid-cell size. Because fire is modeled as a physical process, the assumption of a homogeneous fuel bed is critical. In a spatial application of Rothermel’s model, cells must be small enough that fuel characteristics are uniform within each cell (Frandsen and Andrews 1979). Similarly, the time step in a physical model should be small enough to capture the dynamics of a spreading fire front. In a mountainous terrain, fuel drying rates are affected by elevation, wind, slope, aspect, and canopy cover, and a daily sequence of high and low temperature (Fowler and Asleson 1984, Rothermel et.al. 1986), each of which varies among grid cells. We encountered computational difficulties in directly applying Rothermel’s model to a finely gridded landscape. In contrast, Burrows’ (1988) spatial model for a chaparral landscape avoided much of this complexity because (1) it ignord spatial variation in drying rates; and (2) fuel characteristics could be described by a few discrete types in a chaparral vegetation mosiac.

With some simplifying assumptions, these computational difficulties could be eased. The resulting model, however, would still contain many unknown parameters. Fuel and weather parameters would have to be assigned to each grid cell, over many small-time steps. In addition, some method of conditioning spread probability on spread rate must be assumed. Also, Rothermel’s spread equations, when used to simulate patterns in landscapes, lack a mechanism for simulating major, stand replacing fires. Neither long-term drought nor crown fires are adequately modeled.

Based on the difficulty of developing relevant parameters, we concluded that mechanistic fire models such as Rothermel’s model and its variants are too detailed to apply realistically on a landscape scale. Rather, we believe that some statistical description and simulation of fire patterns will be (1) easier to describe (2) more understandable; (3) faster to implement; (4) more reliable. Our method could retain a several modeling properties. First, the proportion of forest burned each year should be consistent with historical data. Second, the amount of forest burned each year should respond appropriately to climatic shifts. Third, the location of the burned areas should be consistent with stratified data showing relative burn probabilities in various elevation and rainfall zones, slopes and aspects. Fourth, the distribution of fire sizes, edge to area ratios, frequencies, and intensities, should be consistent with observed patterns.

Modeling fire pattern directly

The need to make models discrete in space and time relates to the arguments suggested by hierarchy theory for appropriate choice of scale. In this model, we were interested in landscape patterns that result from fires, not the short term dynamics of a single fire front as it occurs. Other approaches to modeling disturbance in landscape focus more directly on the patterns, and less on the physics, of the disturbance event itself. Baker et.al. (1991) describe a model that expresses a landscape disturbance regime as a distribution of patch sizes. The parameters of the distribution (negative exponential) vary under the influence of weather and landscape attributes, such as the time since last disturbance. Agee and Flewelling (1983) developed a fire-cycle model for the Olympic National Park, based on statistical relationships, in which fire size was expressed as a function of droughtiness.

Statistically, modelling a disturbance regime requires knowledge of the distribution of various attributes of the disturbance regime in space and time (Baker 1992). The size distributions for fires have been described as negative exponential (van Wagtentonk 1986, Baker 1989) or power function (Minnich 1983) distributions. Several investigators have mapped historical fire patterns and estimated the proportion of study areas burned over a time-series of years (Heinselman 1973, Romme 1982, Clark 1990). The distribution of shapes of disturbance events should also be considered. Anderson (1983) fit a double ellipse model to wind-driven fire size and shape. His model has been incorporated into the Rothermel et.al. (1986) model to predict fire perimeter, area, and spread patterns. In a simulation model of fire spread in non-uniform fuels, Green (1983) found that fire shapes were irregular and often non-elliptical. The irregularity of fire shapes due to variations in local topography and weather in Sierra Nevada red fir forests has been observed by Kilgore (1971). A mapping of historical fires in northwestern Minnesota also suggested irregular, patchy fires (Clark 1990).

Temporal distributions of fire events must also be understood if fire patterns are to be modeled statistically. The distribution of fire return intervals has been empirically fit to a Weibull distribution (Johnson and Van Wagner 1985), which changes in form over time with climatic shifts (Clark 1989, Swetnam 1993). Many field studies of fire return intervals only report a mean and a range (e.g. Martin 1982, Agee et. al. 1990), which are inadequate statistics for deriving an asymmetrical distribution. Swetnam (1993) found that fire size in giant sequoia groves decayed exponentially with fire frequency.

Finally, models must reflect the spatial arrangement of fires of varying intensity. Fire effects such as tree mortality and removal of biomass are affected by scorch height, which is a function of fire intensity (Brown et. al. 1985, Ryan and Reinhardt 1988). Both fire probability (Fowler and Asleson 1984) and intensity (Kilgore 1973) vary considerably according to site characteristics.

Statistical fire modeling

Various statistical methods have been used to describe and model vegetation patterns. Logistic regressions, which include neighborhood effects, have been fit to fire probability data in the San Jacinto Mountains (Chou et. al. 1990). Point pattern analysis (Greig-Smith 1964, Pielou 1977) has been used to describe levels of contagion in plant communities (Bonnicksen and Stone 1982). As the name point pattern suggests, these analyses are typically used to test departure from random dispersion at the scale of individual trees. Geostatistical methods have been used to simulate spatial patterns in ecology (Rossi et.al. 1993), by expressing spatial auto-correlation as a function of distance.

The largest study of the statistics of fire pattern to date covered an 85-year fire record for seven National Forests in the Sierra Nevada (McKelvey and Busse 1996). Using logistic regression methods, McKelvey and Busse (1996) linked fire occurrence to topographic features, principally elevation. In addition, McKelvey and Busse (1996) described the size-distribution of fires, and demonstrated their correlation to seasonal weather patterns both at the scale of the entire Sierra Nevada and within the context of local topography.

Markovian modeling of contagion

Markovian models have frequently been used to simulate landscape change (see Baker 1989 for a review). Usually such models are first-order stationary models. That is, the probability of a particular outcome depends only on the current state and not on the history of previous states, and transition probabilities do not change over time. An important modification of the Markov chain model is allowing non-stationary transitions, which may be functions of variables such as weather or successional stage.

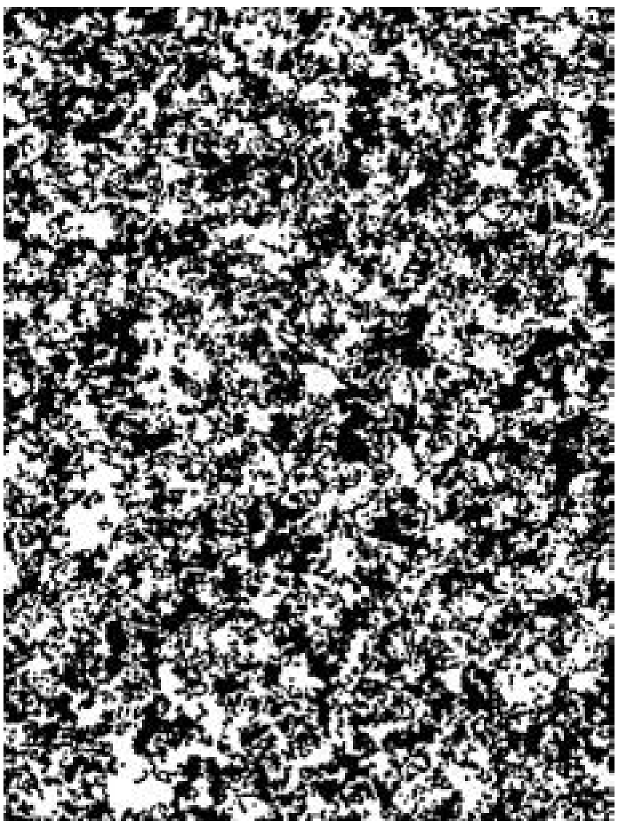

Figure 2. Contagion patterns with moderate contagion and 50% of the landscape burned.

Typically, Markovian models are used to simulate change over time and ignore spatial effects. An exception is Turner's (1987) model, in which transition probabilities were conditioned on the state of neighboring cells. Markovian models may also be used to simulate patterns in space alone. An example is Catchpole's (1987) one-dimensional model of fire spread through a heterogeneous fuel bed. Spatial dependence in fuel types was simulated by conditioning the fuel type of each cell on the fuel type of its neighbor.

SFS - the Statistical Fire Simulator

The theoretical basis for SFS

We have developed a spatial Markovian model in two-dimensions, which retains several of these desirable properties, yet is very simple to implement. It is based on a one-dimensional Markov model, and the spatial implementation involves projecting the one-dimensional version into space by using a space-filling curve.

In the simplest implementation of the one-dimensional version, burn probabilities are assumed spatially and temporally constant. Two parameters are used as inputs. The first is the proportion of the landscape *B* burned each year. The second is a clustering parameter *C*, indicating neighborhood effects.

The clustering parameter indicates the probability that a cell will be burned by a fire front given that a neighboring cell was burned. The one step transitions are specified by the matrix:

State	*Burned*	*Unburned*
Burned	C	$1 - C$
Unburned	$\frac{B(1 - C)}{1 - B}$	$\frac{1 - 2B + BC}{1 - B}$

Changing the parameters *B* and *C* changes the pattern of runs of burned cells (Figures 2 and 3). Unlike most Markov models used in ecology, the one-step transition probabilities indicate transitions in space, rather than time. Unlike contagion models, this model is not a mechanistic model of the spread of a fire event. It is a method for resolving spatial patterns created by multiple fire events occurring in a single year or block of years. Valid combinations of *C* and *B* are those for which $0 < U < 1$, where *U* is cell [2,2] of the matrix (above). Importantly, valid solutions for *U* exist for all $C > B$, that is, for all levels of clustering greater than random.

The assumption of homogeneity in burn probabilities can be relaxed by expressing *B* as function of location and time: $B(x, t)$. This simple adjustment allows for changes in burn frequency due to influences such as climate shifts, vegetation, elevation, slope, and aspect. Figure 4 shows how fire patterns change given constant *C* but spatially variable *B*. *B* is 0.5 on the left half of Figure 4 and 0.1 on the right half. Similarly, *C* can vary spatially. In Figure 5, *B* is constant and *C* changes. Lastly, because burned and unburned areas are resolved within a specific time-period, both *B* and *C* can vary temporally, and, if necessary, be altered by burning patterns from previous time periods.

Figure 3. Contagion patterns with high contagion and 50% of the landscape burned.

The primary appeal of this method, as opposed to statistical models based on ignition and fire spread, is that both ignition and spread rates change the overall frequency of fire on the landscape. Small shifts in contagion factors lead to large differences in the area burned. Generating fires, which match both spatial size patterns and burn an appropriate proportion of the landscape, requires very fine balancing of ignitions and spread rates. Using the methods described above, *B* is completely separate from *C*. In Figures 1 and 2, for instance, approximately the same propor-

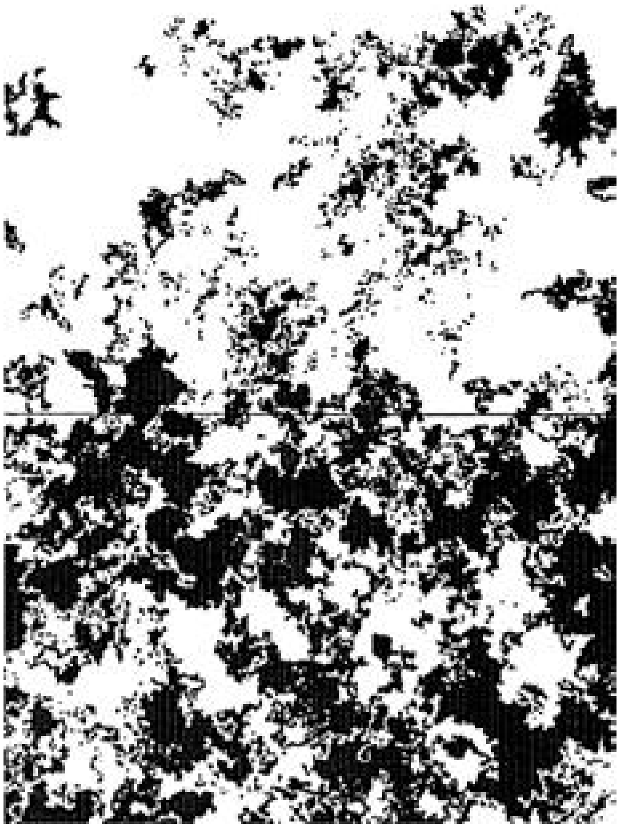

Figure 4. Contagion patterns with 50% of the landscape burned on the top half of the map and 10% burned on the bottom half. At the boundary area between these two background probabilities, the area burned is intermediate between 10% and 50%.

tion of the map burned. This separation means that if we have good estimates of *B*, derived from historical data, we are free to modify *C* to match historical fire-size patterns without worrying about deforming the location and frequency of the fires.

Two-dimensional application: filling space

The method is extended into two-dimensions by using a random walk to fill an area with a one-dimensional sequence of states (Burned/Unburned), subject to the constraint that each cell in the plane is entered exactly once. This method preserves the property that a proportion *B* of the landscape is burned. However, our understanding of the parameter *C* is altered by the use of a one-dimensional walk to fill space. For a given cell (*x*,*y*) in the landscape, two of its four neighbors are actually 'adjacent' from the point of view of the one-dimensional process used to fill space—the cell entered immediately before and immediately after. For these cells, the conditional probability of burning given that (*x*,*y*) burns is *C*. The probability that the other two neighbors are burned given that (*x*,*y*) is burned is different from *C*. This probability is bounded by *B*, the unconditional probability of burning, and *C*, the probability of burning given that the last cell entered burned.

The parameter *C*, if carefully chosen, can provide a pattern of burns that preserves the properties suggested by the one-dimensional model: a known proportion *B* of landscape burned, and a known conditional probability *P* of burning given that any neighboring cell is burned. A lower bound for *P* is (*B* + *C*)/2: the average of the unconditional probability of burning and the known conditional probability of burning for the two cells which are actually 'adjacent' in the one-dimensional walk. If *C* > *B*, *P* will be greater than (*B*+*C*)/2, because of the probability of being within a run of burned cells when a nearby cell is reached. An upper bound for *P* is *C*. the probability *P* can be calculated as:

$$P(X \mid X_0) = \sum_{n=1}^{\infty} P(x_0 + n \mid x_0) f(n)$$

where $P(x \mid x_0)$ is the probability that a cell x neighboring cell x_0 in any of the four directions is burned given that cell x_0 burns. $P(x_0 + n \mid x_0)$ is the probability that a cell entered n steps after cell x_0 burns given that cell x_0 burns, and f(n) is the probability that a cell adjacent to cell x_0 is entered at step $x + n$ or $x - n$. $P(x_0 + n \mid x_0)$ is calculated by taking element [1,1] of the nth power of the single-step probability matrix (Ross 1989). This power is only computed until the element [1,1] of the matrix converges to a steady state, which is the independent probability of burning B. Thus, the sum that must be taken to calculate P is a finite sum. The probability f(n) is calculated by simulation, but must only be calculated once, as it is not a function of B or C. The probability P is therefore completely determined by B and C. If a desired P and B are specified, the appropriate parameter C can be determined by inverting the function relating P to B and C.

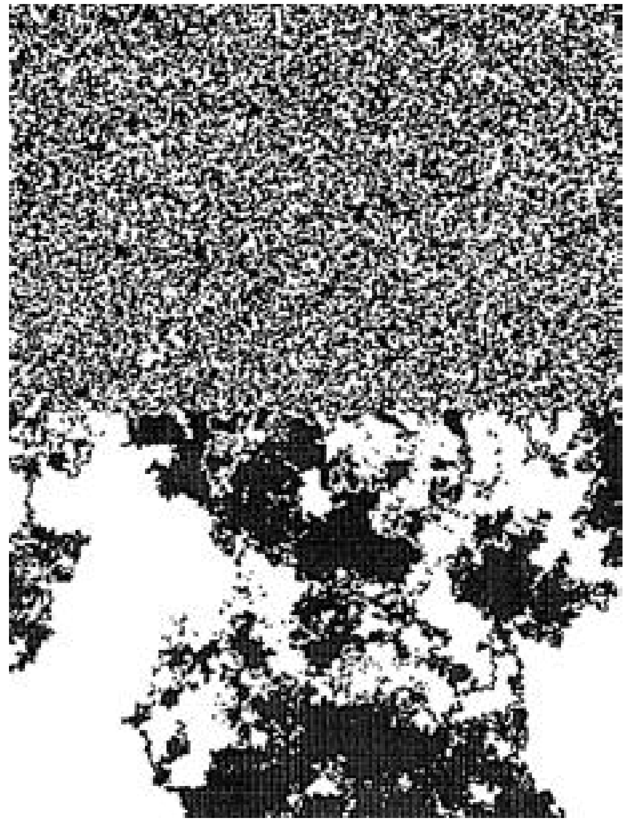

Figure 5.Contagion patterns with high contagion on the top and low contagion on the bottom. Fifty percent of the map area is burned on both the top and bottom sides of the map.

The method described can be used to produce patterns that have many of the desired properties listed above. By expressing B as a function of space and time $B(x,y,t)$, we can ensure that the appropriate proportion of the landscape is burned for a given climatic regime, vegetation type, aspect, and elevation. By manipulating the parameter C, we can create spatial patterns with known statistical properties, such as patch-size distributions and edge-to-area ratios. Only two parameters must be manipulated, decreasing error propagation. However, we can make these two parameters respond appropriately to field data as it accumulates, by stratifying their values based on landscape attributes.

Applying SFS to landscapes

Probabilities of burning and contagion factors will not be uniform on a landscape. The conditional-probability-based approaches stated above can be resolved in non-uniform landscapes, but there will be subtle, but important changes in the local pattern of fire due to juxtaposition of high and low burn probabilities. Areas of high fire probability will produce more fires and due to contagion effects, those fires will spread to adjacent areas of lower burn probability. Similarly, areas that have high fire probabilities, but are adjacent to areas that seldom burn, will burn less than expected.

These effects are not unwelcome and match observed fire behavior: the forest at the top of a brush field may burn more frequently than other similar forests because fires which start in the brush spread into

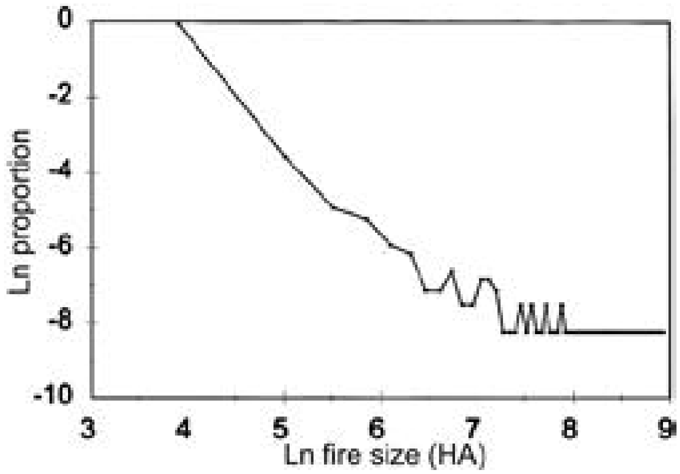

Figure 6. Simulated fire distribution with contagion decreasing as a linear function of fire probability. Compare with McKelvey and Busse (1996; Figure 1).

the adjacent forest. However, they do pose additional difficulties for duplicating background fire frequencies. Fire occurrence probabilities based on historical fire data are already the product of both background ignition probabilities and of contagion. Hence, by starting with these maps and adding additional contagion factors we cause fire to "spread out" beyond the range of the historic fires. It should be possible to force conformity between modeled and historic fires by iteratively changing the background probability map until the simulated occurrence patterns match the original fire occurrence map.

Determining the probability of fire

Matching historic fire probabilities only makes sense if the probabilities are stationary in time. If the probability of fire occurrence changes with shifts in vegetation, then these probabilities will directly feedback to the fire activity and there will be no underlying pattern to match.

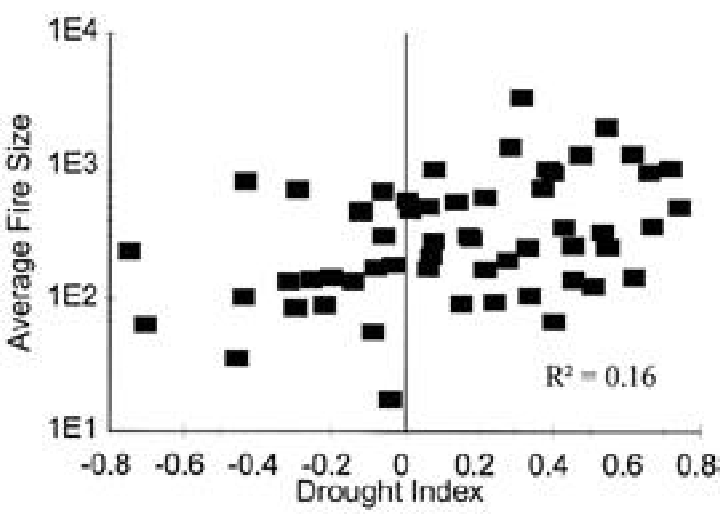

Figure 7. The relationship between average fire size and seasonal drought for the Sierra Nevada and years 1933-1989. See McKelvey and Busse (1996) for an explanation of the drought index.

A study of fire in the 20th century Sierra Nevada demonstrated that fire patterns have been static throughout the century (McKelvey and Busse 1996,) although vegetation characteristics have undoubtedly changed during this period. These fire patterns were adequately described by topography and weather. Periodic increases in fire activity correlate with dry conditions (McKelvey and Busse 1996). Similarly, long-term patterns of presettlement fire are consistent (See Generating Presettlement Fire Patterns,), with fluctuations largely controlled by weather (Swetnam 1993).

Exploring fuel limitations

On a smaller scale, the interactions of fire and vegetation could result in a fuels-limited system in which the probability of a site burning was reduced for some period after a fire occurred. In the Sierra

Nevada, McKelvey and Busse found that reburn patterns for 20th century fires were largely random. In addition, a re-analysis of Swetnam's (1992) fire data for several giant sequoia groves showed a random pattern in these groves, although the groves had very short fire return periods (5-10 years) and often burned every year. (See Generating Presettlement Fire Patterns). Based on these data, and particularly for the Sierra Nevada, it is sufficient to model random reburns.

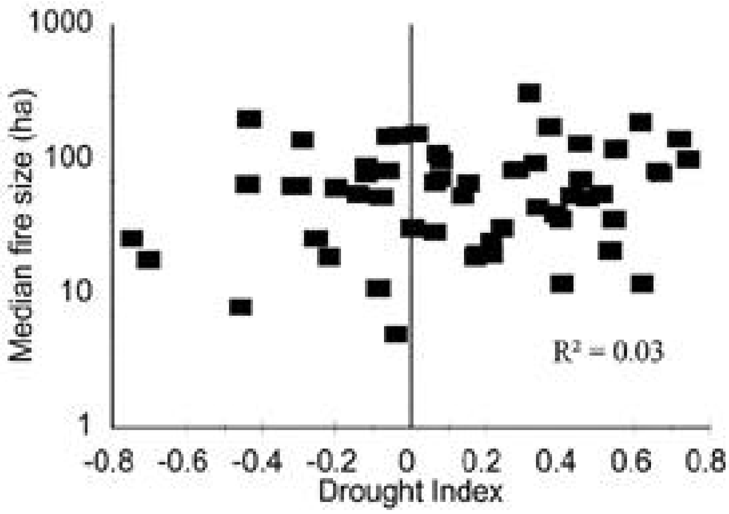

Figure 8. The relationship between median fire size and seasonal drought for the Sierra Nevada and years 1933-1989. See McKelvey and Busse (1996) for an explanation of the drought index.

Modeling fire size

Reported fire size distributions tend to be linear in log-log space (Minnich 1983), with many large and few small fires. This pattern is true for fires in the Sierra Nevada in the 20th century as well (McKelvey and Busse 1996). The runs of fire produced by the conditional probability model also produce many small and few large fires. However, the pattern of decline is exponential rather than a power function if C is constant. This is because the contagion rules modify the "runs" structure inherent to random data. If we make the simple assumption that contagion declines where general fire risk is low, then the conditional probability model produces fire distribution patterns which are straight in log-log space (Figure 6) with the slope of the line being determined by C.

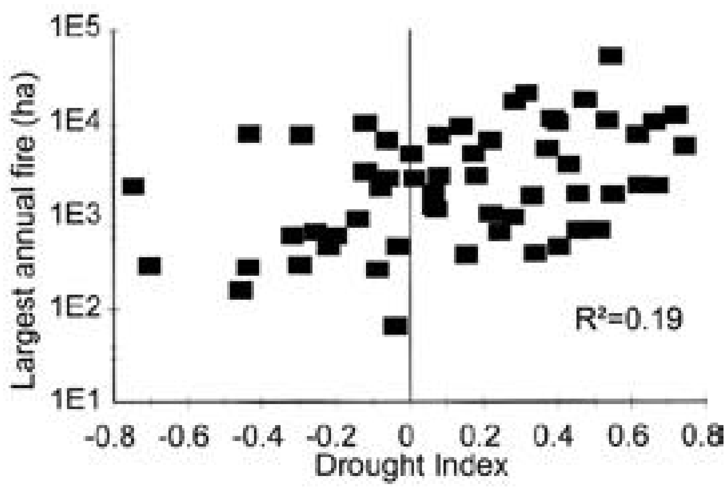

Figure 9. The relationship between maximum annual fire size and seasonal drought for the Sierra Nevada and years 1933-1989. See McKelvey and Busse (1996) for an explanation of the drought index.

Model flexibility-weather related effects

Application of these statistical models to past and future fire scenarios presents several potential problems. Many center on the lack of flexibility—the models mimic historical patterns rather than account for differences due to changes in management policy. It is true that some management approaches that would be difficult to model statistically (fuel

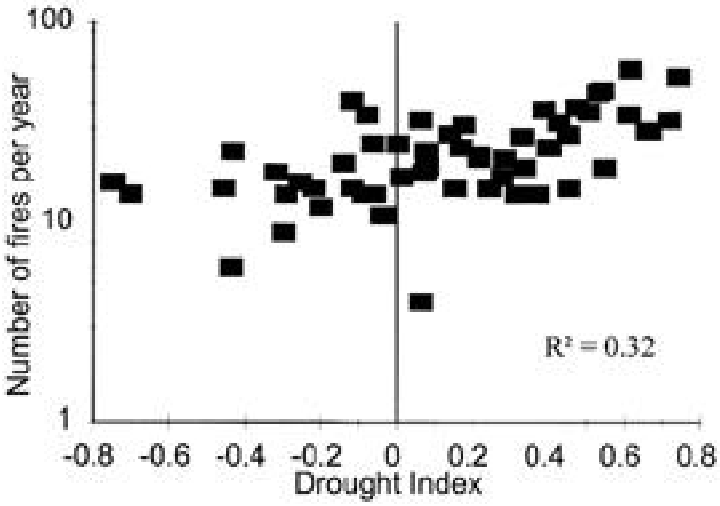

Figure 10. The relationship between number of fires and seasonal drought for the Sierra Nevada and years 1933-1989. See McKelvey and Busse (1996) for an explanation of the drought index.

breaks, for instance). However, fire patterns have been stable over the last 85 years (McKelvey and Busse 1996). The vegetation in the Sierra also has changed in that interval far more than we might envision being associated with a shift in vegetation-management policies.

In fact, many temporal shifts can be modeled rather simply using these methods. As an example, we might ask what the change in fire patterns might be if the climate turned drier. For evidence, we can look at the statistical relationships between fire and drought in the Sierra Nevada from 1933-1989. Total acreage was positively correlated with hot, dry years (McKelvey and Busse 1996). Closer examination, showed that hot dry years were not strongly associated with fire size, whether we look at average (Figure 7) or median fire size (Figure 8), or largest annual fire (Figure 9). The primary reason that more acres burn in hot dry years is that there are more fires (Figure 10). Based on these data, it is reasonable to model changes in weather as an overall either increase or decrease (dry or wet) in fire occurrence at all elevations. There is, however, little evidence to support a change in fire size, which in this modeling context is controlled by *C*.

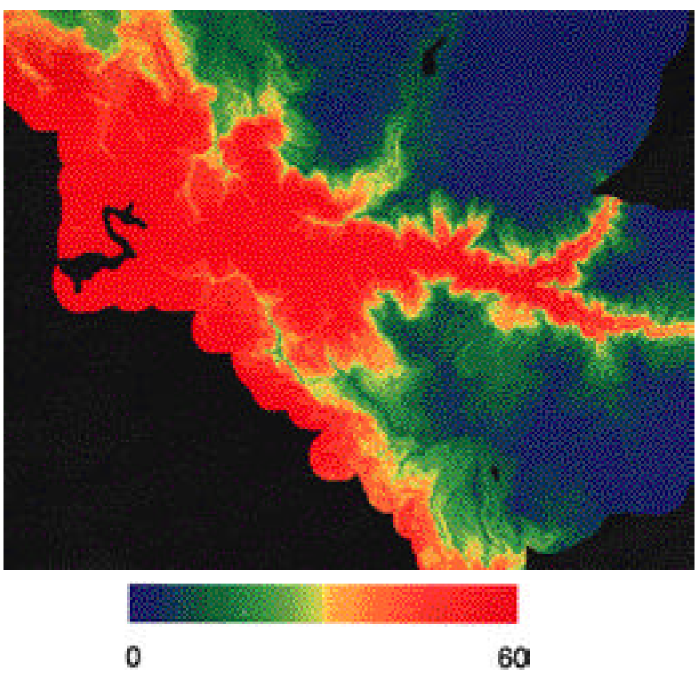

Figure 11. Background fire probability for an area in the southern Sierra Nevada and for fires in the 20th century (See McKelvey and Busse 1996; Plate 3).

Application of SFS to an actual landscape

As a trial application, we utilized a portion of the fire probability map developed to describe fire occurrence patterns the 20th century Sierra Nevada (See McKelvey and Busse 1996, Plate 3) (Figure 11). Figure 12 shows an example of an 85-year run on this landscape using SFS with moderate contagion. To determine the effects of varying contagion on simulated fire occurrence patterns, we simulated 10,000-year runs with moderate contagion (as in Figure 12) and very high contagion (See Figure 3). Figures 13 and 14 portray the results of these simulations. With moderate contagion, the simulated fire frequencies are very close to the background probability map (Figure 11). For high contagion fires, the adjacency effects cause the fire to carry into higher elevation zones, and to shrink away from the map edges (map edges have fire probabilities of 0.0).

Discussion

We believe that our fire modeling approach has many desirable features. Since we developed the conceptual framework for this type of modeling in 1994, we have demonstrated its application as a methodology and its use at the landscape level. In addition, we have developed a working prototype model, and have created two potential risk maps for the Sierra Nevada, one representing 20th century fire (McKelvey and Busse 1996) and one representing presettlement fires (Generating Presettlement Fire Patterns).

The model is still in need of significant improvements prior to application in a management context. First, the rules for contagion should be formally two-dimensional, rather than using a space-filling implementation of one-dimensional contagion. This will allow *C* to be directly linked to two-dimensional shapes. Second, we need to build an iterative process to control the effects of contagion on simulated fire distribution so that the simulated patterns better match the background probabilities. Lastly, we need to

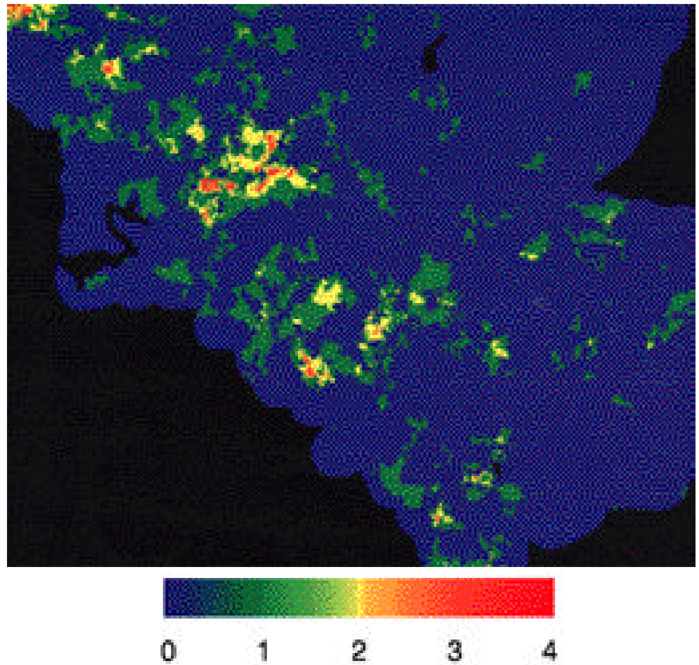

Figure 12. Simulation of an 85-year fire pattern on the landscape shown in Figure 11. Colors represent the number of times an area reburned.

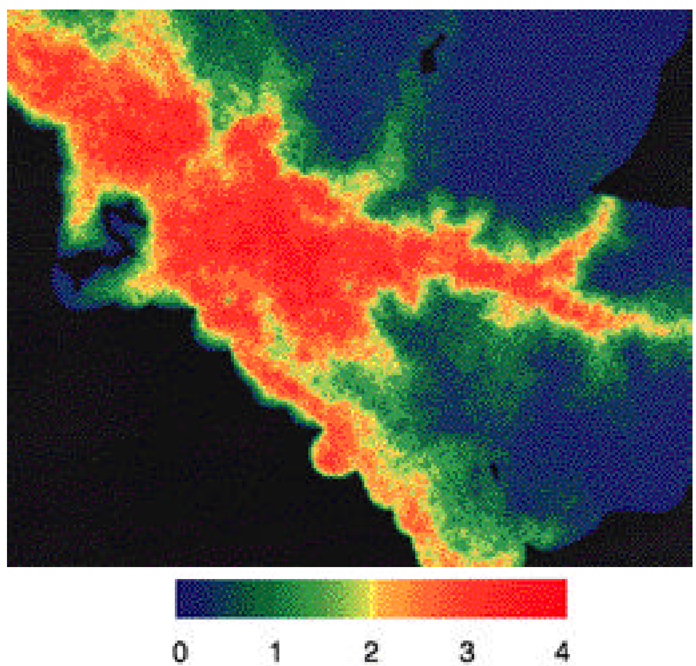

Figure 13. Emergent fire patterns based on a 10,000-year simulation with moderate contagion (See Figure 12), and using the landscape shown in Figure 11. Colors represent the number of times a site reburned.

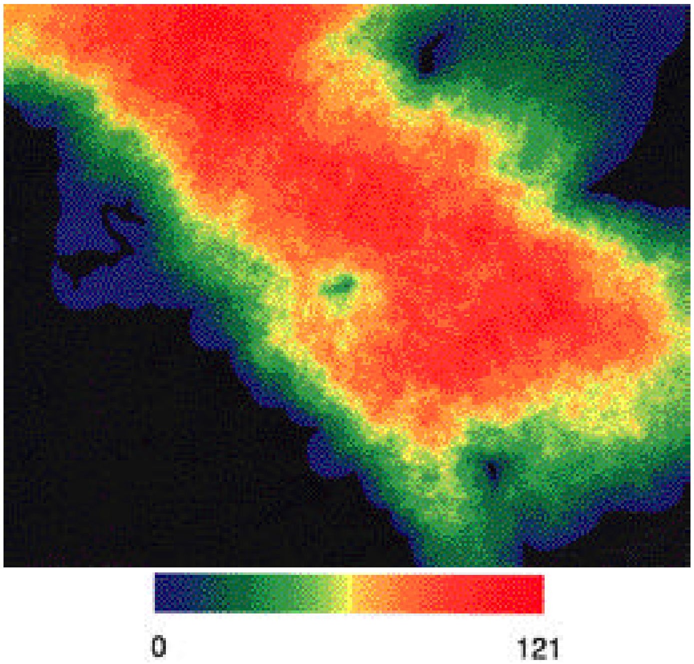

Figure 14. Emergent fire patterns based on a 10,000-year simulation with high contagion (See Figure 3), and using the landscape shown in Figure 11. Colors represent the number of times a site reburned. Note the movement of fire up-slope and away from the map-edges.

determine rules controlling fire effects in those areas that burn.

These current limitations, in contrast to the many weaknesses associated with expansions of Rothermel's (1972) models, are much easier to address. The first two are relatively simple internal modeling issues. The third can be most easily solved by relating specific fire weather to fire size using fire record data. There is work currently in progress by Larry Bradshaw (Larry Bradshaw, USFS Fire Laboratory, Missoula Montana, pers. comm.) to utilize the Forest Service fire record data held in Kansas City to develop these relationships.

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